UNIVERSITY of DAYTON

VISION LAB

Center of Excellence for Computer Vision and Wide Area Surveillance Research

Patrick Martell

Advisor: Dr. Vijayan Asari

CNN Based HAP Net for Deep Learning

Objective

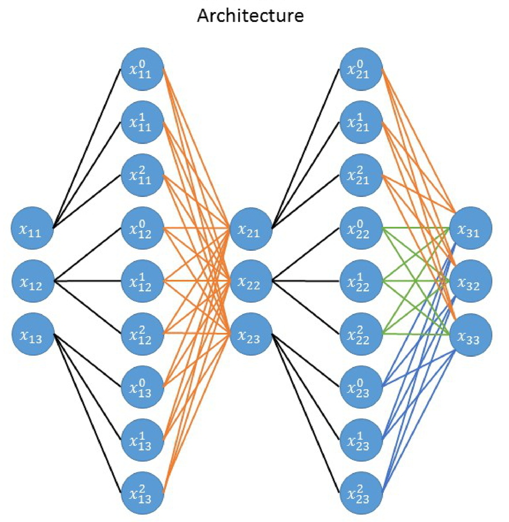
While HAP Net yielded good results, combining these strategies with CNN based methods should result in a higher precision and recall scores.

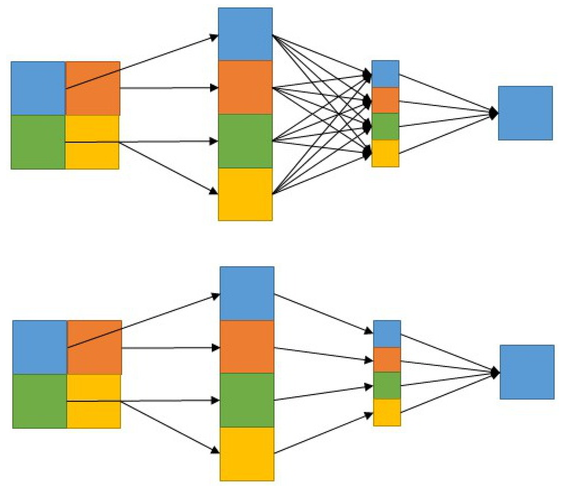
Purpose

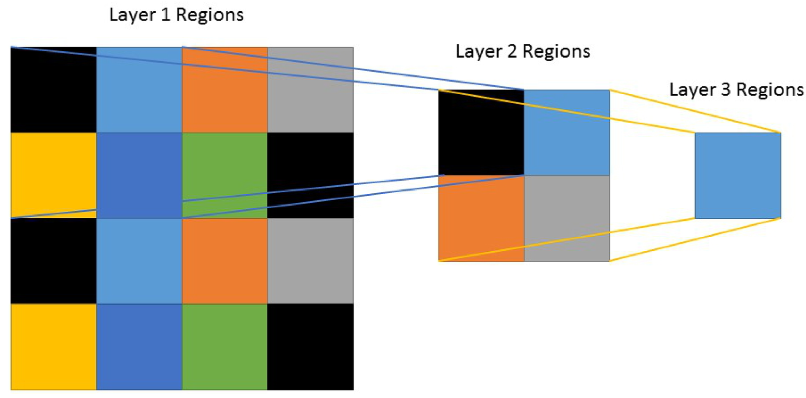
This program shows great promise in the field of image classification, ranging from hand written digits to civilian vehicles. Additionally, there is potential within facial recognition and other similar recognition tasks.

HAP Net Technical Description

- Polynomial Weighting Scheme
- Region-based setup enables local connectivity
- Modularity of design allows for modifications to cater the design for each dataset.
- Training times around 8 to 12 hours on a standard laptop



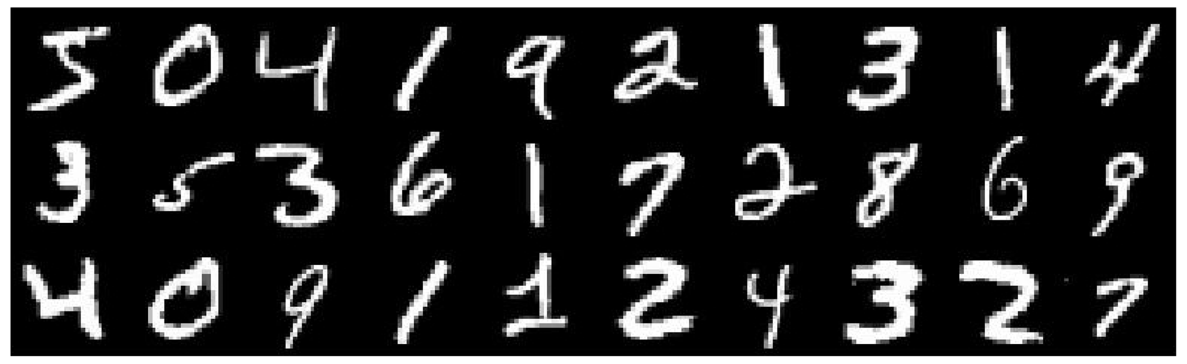




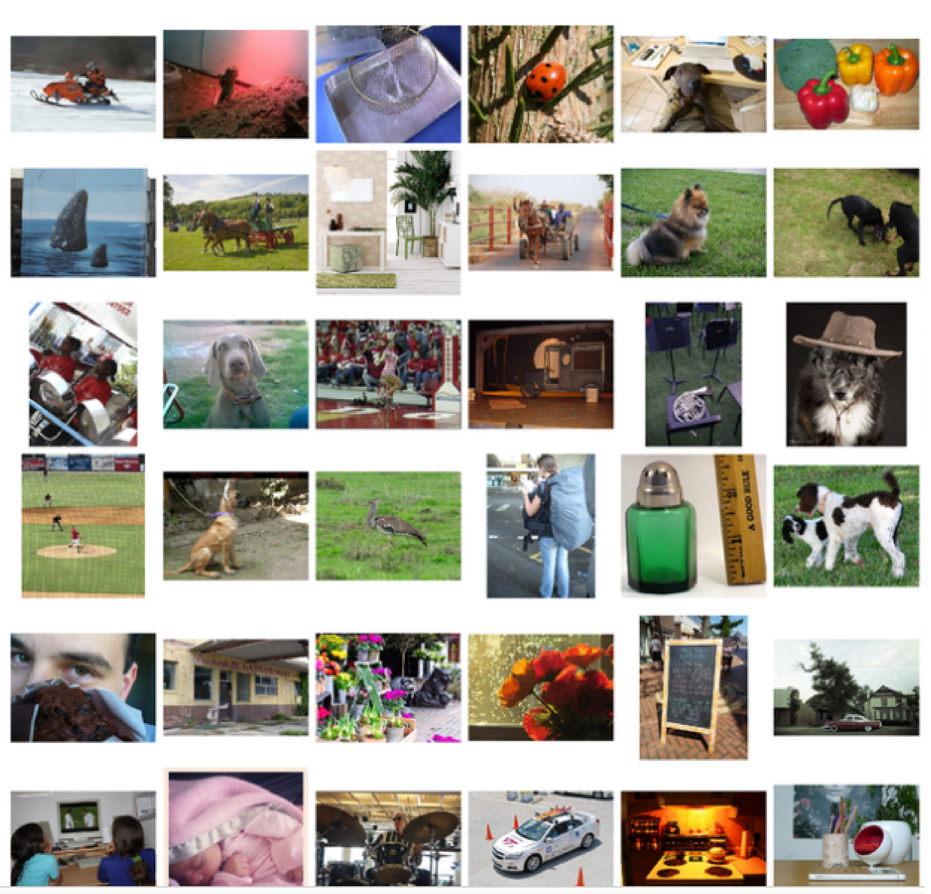
HAP Net Results - MNIST

Method	Test Error Rate
HAP Net Order 2 1 Region 500 + 150 HU	1.7
HAP Net Order 2 16 Region 500 + 150 HU	2.05
HAP Net Order 2 4 Region 500 + 150 HU	1.53
HAP Net Order 1 4 Region 500 + 150 HU	1.88
HAP Net Order 3 4 Region 500 + 150 HU	2.13

Method	Test Error Rate
HAP Net Special Configuration 3	1.54
HAP Net Order 2 Special Configuration 4	1.33
HAP Net 500 – 500 – 2000 – 30 HU	1.08
Convolutional Net LeNet-4	1.1

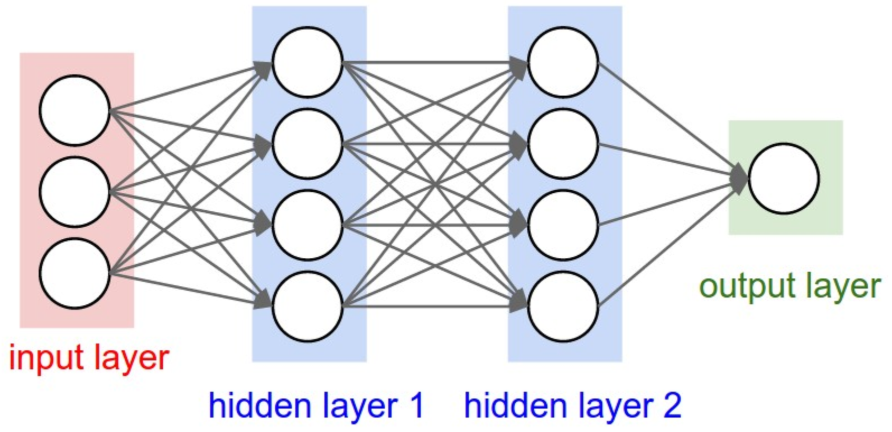


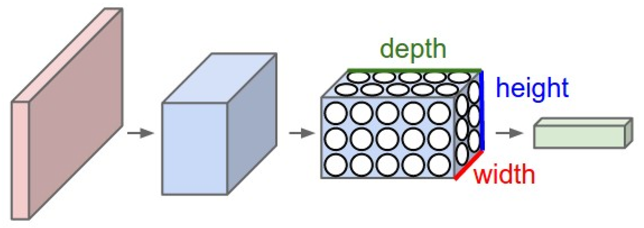
CNN Results – ILSVRC (1000 classes)

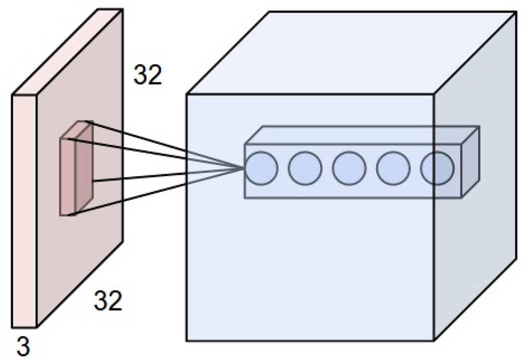


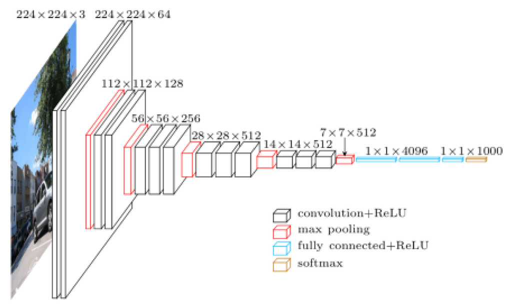
Network	Top 5 Test Error Rate
AlexNet	18.9
GoogLeNet	6.65
VGGNet	7.32
ResNet	3.57
ZFNet	13.5

Convolutional Neural Networks









- Weights are derived from convolution filters.
- Local Connectivity Inherent in design.
- Design has the ability to describe many different datasets very well.
- Training times vary, but can take very long periods of time.

CNN Based HAP Net – Future Plans

- Polynomial Representation of CNN weights
- HAP Net regions replaced with convolution filters
- Combining convolutions within each region of HAP Net
- Regions able to contain overlap and do not need to be a square number
- More flexibility in the object's location within the image

References: Name, “Title,” in Where, year.
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UNIVERSITY of DAYTON
Vision Lab
Kettering Laboratories
300 College Park
Dayton, OH 45469-0232

UD VISION LAB
www.visionlab.udayton.edu

Dr. Vijayan Asari
Director
(937) 229-4504
VAsari1@udayton.edu